

RESEARCH REPORT

A Better Measure of Mortgage Application Denial Rates

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A Better Measure of Mortgage Application Denial Rates

The mortgage application denial rate, which is calculated from Home Mortgage Disclosure Act (HMDA) data,¹ is often used as a measure of credit accessibility. The problem is, denial rates depend on the composition of borrowers along with how loose or tight credit standards are. Higher denial rates can be the result of either a tighter credit environment or an increase in applications by weaker-credit borrowers.

For example, denial rates were much higher in 2007 than they are now, after the financial crisis. If interpreted literally, this pattern means that credit was tighter in 2007 than it is today. We know this is not the case. In 2007, more applicants with weaker credit profiles applied for mortgages, so demand was higher.

A better measure of the denial rate would hold the credit profile of the application pool constant. Creating a constant application pool poses an analytic challenge: researchers have information about the credit characteristics of only those who receive loans, not those whose loan applications are denied.²

This paper discusses how to construct a better measure of the mortgage application denial rate that accounts for shifts in the composition of the applicant pool over time. That analysis gives us very rich results. In particular, our measure of the denial rate is higher than the observed denial rate. And, most of the racial and ethnic gaps in denial rates disappear among low-credit-profile applicants.

Calculating the Real Denial Rate for Low-Credit-Profile Applicants

Defining the Real Denial Rate and the Observed Denial Rate

To construct a better measure of the denial rate, we divide applicants into two categories: high credit profile, or HCP, and low credit profile, or LCP. HCP applicants are those whose credit profiles are strong

enough that their mortgage applications are unlikely to be denied by lenders. Thus, by definition, HCP applicants have a denial rate of zero.

If the number of HCP applicants receiving loans equals the number of HCP applicants applying for loans, then the difference between the total number of mortgage applicants and the number of HCP applicants equals the number of applicants whose credit profiles are *not* strong enough to have a zero denial rate. We call this group the LCP applicants.

The total number of denied applicants divided by the number of LCP applicants equals the denial rate of LCP applicants. We call this the real denial rate, or **RDR**, versus the traditional denial rate of all applicants (HCP and LCP), which we call the observed denial rate, or **ODR**.

By eliminating those whose mortgage applications are unlikely to be denied and focusing on those with weaker credit records, the RDR provides a much more accurate picture of credit access than the ODR does.

Defining Low Credit Profiles

What makes a consumer low-credit-profile? A consumer's credit profile is usually measured along a number of different dimensions, such as loan-to-value (LTV) ratio, credit score (FICO), and debt-to-income (DTI) ratio. Lenders use these factors to measure the consumer's credit risk and make lending decisions. Lenders treat consumers with different combinations of these risk factors but equal credit risk as similarly creditworthy. Consumers with higher credit risk are more likely LCP than those with lower credit risk. So if we know the consumer's expected credit risk, we can assign the consumer a probability of being LCP.

We can use historical mortgage default rates to construct "lookup" tables, which contain the actual default rates for 360 different risk combinations of FICO, LTV, DTI, and product type (see Li and Goodman 2014 for examples). Then, for loans originated at any given time, their expected default risk equals the actual default rate of the loans with matching risk factors that were used to construct the lookup tables.

To transform the expected default risk into the probability of being LCP, we

- ▾ assign zero probability of being LCP to consumers who intend to apply for loans without risky features and who have a FICO score greater than 700, LTV less than 78, and DTI less than 30.

Their amount of expected default risk is considered the lower bound. Other consumers with expected default risk equal or less than this lower bound receive 0 probability of being LCP.

- ▼ assign 100 percent probability of being LCP to consumers who intend to apply for loans without risky features and who have a FICO score less than 580, LTV greater than 95, and DTI greater than 50. Their amount of expected default risk is considered the upper bound. Other consumers with expected default risk equal or greater than this upper bound receive 100 percent probability of being LCP.
- ▼ make a linear transformation on expected default risk for consumers with credit risk in between the upper and lower bounds so higher expected default risk always leads to a higher probability of being LCP, and vice versa; so the probability of being LCP approaches 100 percent as the expected default risk approaches the upper bound; and so the probability of being LCP approaches 0 as the expected default risk approaches the lower bound.

The probability of being LCP for 360 different risk combinations of FICO, LTV, DTI, and product type is shown in table A.1 in the appendix. We assume all loans in the bucket are homogenous. Thus, using this table, we can assign a probability of being LCP to any combination of borrower–loan characteristics in the CoreLogic database.³

Calculating the RDR

With a working definition of low-credit-profile, we illustrate the calculation of the RDR in table 1, using HMDA data, CoreLogic data, and a dataset that matches the two.⁴ All the analyses in this paper are limited to mortgage applications to purchase owner-occupied single-family properties. Any further mentions of loans or loan applications are for such properties.⁵

According to HMDA data, blacks submitted 826,808 mortgage applications in 2006, of which 245,594 were denied by lenders and 581,214 were approved.⁶ So, the traditional denial rate (ODR) for blacks is 30 percent.

According to our matched HMDA and CoreLogic data, 379,729 (65 percent) of the approved applications were from LCP consumers⁷ and 201,485 were from HCP consumers. Since HCP applications are unlikely being denied by lenders, the total number of HCP applications is assumed to be 201,485. Subtracting this number from 826,808 total applications leaves 625,323 (76 percent) LCP applications. All denied applications come from the LCP pool, so the real denial rate (RDR) for LCP applications is 245,594 divided by 625,323, or 39 percent.

The RDR, which is 9 percentage points higher than the ODR, reflects the change in the shares of LCP consumers from the applicant pool to the borrower pool: the share of LCP applications is 76 percent, and the share of LCP borrowers is 65 percent.

Comparing How the RDR and the ODR Measure Credit Accessibility

We calculate the 2013 ODR and RDR for black applicants similarly. The ODR is 24 percent, 6 percentage points lower than in 2006. This result suggests credit was tighter in 2006 than in 2013, which is against our expectations: we would expect denial rates to be lower during the housing boom, with lenders approving loans they don't normally approve, and higher after the financial crisis as the credit box tightened.

Changes in loan applicants' credit profiles explain the counterintuitive results. In 2006, 76 percent of loan applications were by LCP applicants, versus 50 percent in 2013. In the boom years, more LCP consumers were encouraged to submit applications; thus, more of them were rejected. As the credit box tightened after the financial crisis, many LCP consumers were discouraged from applying at all, leading to fewer rejections. These findings again highlight that the ODR is a far-from-perfect measure of credit accessibility, especially for examining changes over time.

Because the RDR measures only the denial rates for LCP applicants, it reveals a more intuitive pattern: the RDR in 2013 is 49 percent, 10 percentage points higher in 2006. Thus, the RDR shows a much tighter credit box post crisis than during the boom years.

The RDR also shows much smaller racial and ethnic gaps in credit accessibility. In 2006 the ODRs for blacks and non-Hispanic whites were 30 and 13 percent, respectively. Black applicants were 2.3 times more likely to be denied credit than non-Hispanic whites. The denial rates for black and white LCP applicants were 39 and 24 percent, respectively, meaning black LCP applicants were 1.6 times more likely to be denied credit than non-Hispanic white LCP applicants. In 2013 the ODRs for black and non-Hispanic whites were 24 and 12 percent, respectively. Black applicants were 2 times more likely to be denied credit than non-Hispanic whites. The RDRs were 49 and 41 percent, respectively, meaning black LCP applicants were only 1.2 times more likely to be denied than non-Hispanic white LCP applicants. We dive deeper into this topic later.

TABLE 1

Calculating the Real Denial Rate

Variable	Variable name	Calculation/ data source	2006		2013	
			Black	Non-Hispanic white	Black	Non-Hispanic white
Total # of loan applications	A	HMDA	826,808	4,235,242	181,536	2,267,454
# of loan applications denied by lenders	B	HMDA	245,594	561,496	43,941	268,822
% of loan applications denied by lenders (observed denial rate)	ODR	= B/A	30%	13%	24%	12%
# of loan applications approved by lenders ^a	C	= A - B	581,214	3,673,746	137,595	1,998,632
% of loans to low credit profiles ^b	D	CoreLogic matched with HMDA	65%	49%	34%	19%
# of approved loan applications by low credit profiles	E	= C × D	379,729	1,811,927	46,543	385,396
# of approved loan applications by high credit profiles	F	= C - E	201,485	1,861,819	91,052	1,613,236
# of loan applications by high credit profiles ^c	G	= F	201,485	1,861,819	91,052	1,613,236
# of denied loan applications by high credit profiles	H	= G - F	0	0	0	0
# of loan applications by low credit profiles	I	= A - G	625,323	2,373,423	90,484	654,218
% of loan applications by low credit profiles	J	= I/A	76%	56%	50%	29%
# of denied loan applications by low credit profiles	K	= B	245,594	561,496	43,941	268,822
% of loan applications by low credit profiles denied by lenders (real denial rate)	RDR	=K/I	39%	24%	49%	41%

Sources: HMDA, CoreLogic, and matched HMDA and CoreLogic data.

Notes: The analysis is limited to owner-occupied purchase mortgage applications. Loan applications by blacks and non-Hispanic whites in 2006 and 2013 are used to illustrate how the RDR is calculated. The raw data for other races or ethnicities, channels, and origination years used for calculating the RDR is available upon request.

^a Includes both originated loans and loan applications approved by the lenders but not accepted by the applicants. The latter accounts for less than 10 percent of approved applications.

^b See page 2 for the definition of low credit profiles.

^c By definition, high credit profiles have no chance being denied of a loan application.

Findings

The RDR Reveals More Intuitive Trends on Credit Accessibility

Instead of being lower in the boom years and higher after the financial crisis, the ODR for the whole mortgage market shows the opposite pattern. The ODR was 24 percent in 1998, dropping until it reached 14 percent in 2002. It then went up through the boom, peaking at 18 percent in 2006, then fell again as the bottom fell out of the market in 2008. Since 2011, it stays at the historic low of 14 percent (table 2 and curve A in figure 1.A).

Table 3 and curve A in figure 1.C explain those unexpected patterns: in the boom years, more LCP consumers were encouraged to submit applications; thus, more of them were likely rejected. As the credit box tightened after the financial crisis, many LCP consumers were discouraged from applying at all, leading to fewer of them likely rejected. In the peak of the boom years, 62 percent of loan applications were by LCP applicants. The LCP share is well below 40 percent after the crisis; in 2013, a historically low 31 percent were LCP applicants, much lower even than the pre-bubble years (1998–2003), when the average share was 48 percent.

By measuring denial rates exclusively for LCP applicants, the RDR shows more intuitive patterns: the average shares of LCP applicants being denied by lenders are 39, 29, and 41 percent, respectively, for the pre-bubble (1998–2003), bubble (2004–07) and post-crisis (2010–13) periods (see table 2 and curve A in figure 1.D). In 2004, an LCP applicant had a 25 percent chance of being denied; in 2013, a similar applicant had a 43 percent chance of being denied.

A lower or higher real denial rate, however, does not necessarily lead to a better financial outcome. A low RDR may reflect an oversupply of bad products, as it did in 20007. Similarly, a high RDR may reflect overly strict credit availability, which is hampering access to credit and curbing economic growth. The optimal RDR is an issue that deserves further study.

TABLE 2

Traditional Denial Rate (ODR) and Real Denial Rate (RDR) by Channel, Race, and Ethnicity

Origination year	ODR															RDR																		
	Conventional					Government					All					Conventional					Government					All								
	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A
1998	54	38	25	12	28	13	11	7	9	9	43	29	22	12	24	78	70	60	42	63	21	18	13	17	15	64	52	50	36	52				
1999	49	35	24	13	26	14	11	8	10	10	39	27	21	12	23	71	63	55	38	57	21	18	14	17	16	57	47	46	34	47				
2000	46	33	22	13	24	17	12	11	10	12	37	26	20	13	22	66	58	48	36	51	26	20	17	17	19	54	45	41	33	43				
2001	37	25	15	11	18	12	11	7	9	8	29	21	14	11	16	60	52	41	35	44	19	17	11	14	13	45	38	32	31	35				
2002	30	21	13	10	14	14	12	8	9	9	25	18	12	10	14	50	41	33	30	36	20	17	12	14	14	39	33	27	28	30				
2003	27	21	13	12	15	15	14	9	10	10	24	19	12	12	14	44	38	31	30	33	21	19	13	15	15	38	33	27	29	29				
2004	24	19	11	14	14	17	16	10	12	12	23	19	11	14	14	36	31	23	28	27	21	20	14	15	16	33	30	22	28	25				
2005	26	22	13	17	16	17	16	10	11	12	26	22	12	17	16	37	32	24	29	27	20	20	13	15	15	35	31	23	29	26				
2006	31	26	14	18	18	16	14	10	10	11	30	26	13	18	18	41	36	25	31	31	19	17	13	13	14	39	36	24	31	29				
2007	35	31	13	19	18	22	19	13	15	15	33	30	13	19	18	50	48	30	40	37	27	25	18	21	21	46	45	28	39	35				
2008	35	31	14	19	17	24	22	13	19	16	29	27	14	19	17	66	66	49	62	54	34	33	23	31	26	46	48	35	54	39				
2009	33	27	13	16	15	22	20	12	17	15	24	22	13	17	15	75	77	65	76	68	36	35	24	33	28	43	43	36	55	39				
2010	30	24	12	15	14	22	20	13	18	15	24	21	13	16	15	70	75	66	74	68	37	36	26	35	29	42	42	37	53	39				
2011	29	23	12	15	14	22	19	13	18	15	24	20	12	16	14	69	69	63	73	65	38	34	27	35	30	44	41	38	54	40				
2012	28	21	11	14	13	23	19	13	19	15	24	19	12	15	14	72	67	63	72	65	40	34	27	36	30	46	41	39	55	41				
2013	26	20	11	14	12	23	19	14	20	16	24	20	12	15	14	75	71	61	70	64	41	35	29	37	32	49	44	41	57	43				
98-03	40	29	18	12	21	14	12	8	10	10	33	23	17	12	19	62	54	44	35	47	21	18	13	16	15	49	41	37	32	39				
04-07	29	25	13	17	17	18	16	11	12	13	28	24	13	17	16	41	37	25	32	30	22	21	14	16	17	39	35	24	32	29				
08-09	34	29	13	18	16	23	21	13	18	15	27	25	13	18	16	71	72	57	69	61	35	34	23	32	27	44	46	35	54	39				
10-13	28	22	12	14	13	23	19	13	19	15	24	20	12	15	14	71	70	63	72	65	39	35	27	36	30	45	42	39	55	41				
Mean	34	26	15	15	17	18	16	11	14	13	29	23	14	15	17	60	56	46	48	49	28	25	18	23	21	45	41	34	40	37				

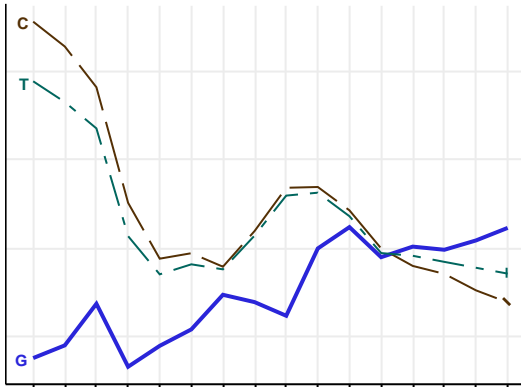
Sources: HMDA, CoreLogic, and the matched HMDA and CoreLogic data.

Notes: The analysis is limited to owner-occupied purchase mortgage applications. B = black; H = Hispanic; W: non-Hispanic white; A = Asian; T = all races and ethnicities.

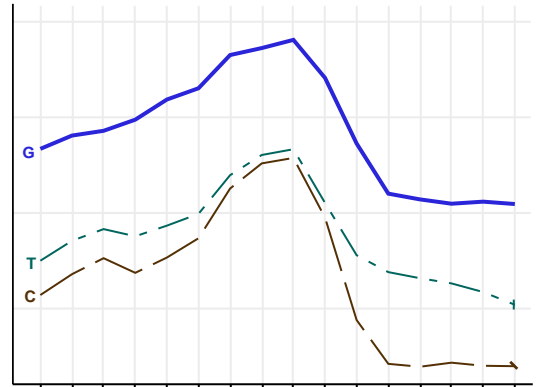
FIGURE 1

Denial Rates and Share of LCP Borrowers and Applicants by Channels

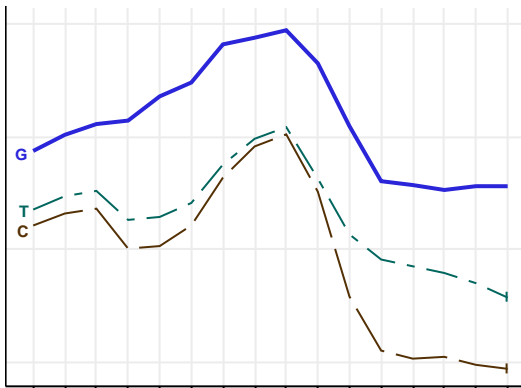
A: tradition denial rate (ODR)



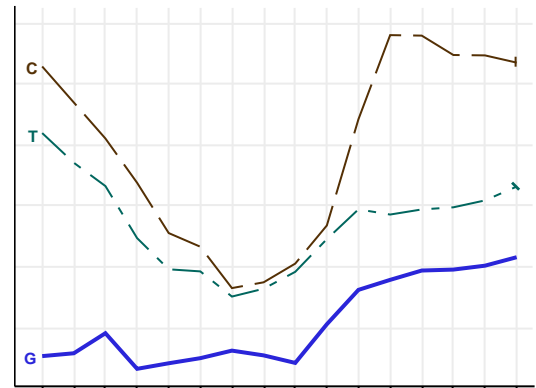
B: share of LCP borrowers



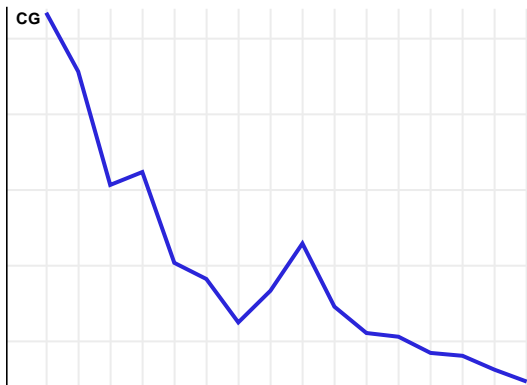
C: share of LCP applicants



D: real denial rate (RDR)



E: ODR ratios



F: RDR ratios.



Sources: CoreLogic, HMDA, matched HMDA and CoreLogic data, and author calculations.

Notes: T = whole mortgage market; C = conventional channel; G = government channel; CG = ratio between C and G.

TABLE 3

Share of Low-Credit-Profile Borrowers and Applicants by Channel, Race, and Ethnicity

Origination year	Borrowers (%)															Applicants (%)																		
	Conventional					Government					All					Conventional					Government					All								
	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A	T	B	H	W	A
1998	32	26	22	20	23	56	53	53	52	53	43	39	28	24	30	69	55	41	30	44	62	58	56	57	57	68	57	44	33	47				
1999	39	31	26	23	27	59	56	56	55	56	48	42	32	27	34	68	55	44	33	46	65	61	59	60	60	68	58	47	36	49				
2000	42	35	29	27	30	59	57	57	56	57	50	44	35	30	37	69	56	45	37	47	66	62	61	60	62	68	58	48	39	50				
2001	39	32	26	24	27	62	59	59	59	59	49	43	33	28	35	61	49	38	33	40	66	64	62	62	63	64	55	42	36	45				
2002	42	37	29	27	31	66	65	63	64	64	51	46	35	30	37	59	50	38	34	41	70	69	66	67	67	63	56	43	37	46				
2003	47	43	33	32	35	68	67	65	66	66	53	49	38	34	40	61	55	41	40	44	73	72	68	70	70	65	59	45	42	48				
2004	57	54	42	42	45	76	74	72	73	73	61	56	45	43	48	68	62	49	51	53	80	78	75	76	76	70	64	51	51	55				
2005	61	59	47	49	50	78	77	73	73	74	63	60	49	49	52	71	68	54	57	58	82	80	76	76	78	72	69	55	57	60				
2006	64	63	47	49	51	80	78	75	75	76	65	63	49	49	53	75	73	54	58	60	83	81	78	77	79	76	73	56	58	62				
2007	52	49	36	35	39	74	71	67	66	68	56	52	39	36	42	69	65	45	47	50	79	77	71	71	73	71	66	47	48	53				
2008	28	23	17	14	17	61	57	53	52	54	48	40	29	20	31	53	47	28	30	32	70	66	59	61	62	63	56	39	35	43				
2009	16	11	8	6	8	49	47	43	42	44	43	38	26	17	27	44	35	20	22	22	60	58	50	52	52	57	51	35	30	38				
2010	19	11	7	6	8	48	46	41	41	43	43	37	24	16	26	43	32	19	20	21	60	57	49	51	51	56	50	34	29	37				
2011	19	13	8	7	8	47	44	41	41	42	41	36	23	16	25	43	33	19	21	21	59	55	48	51	51	55	48	33	29	36				
2012	15	13	7	7	8	45	45	41	42	42	38	34	22	15	23	39	31	18	20	19	58	55	49	53	51	53	47	31	28	34				
2013	12	10	8	7	8	44	44	41	42	42	34	30	19	13	21	35	28	17	19	19	57	55	49	53	51	50	44	29	26	31				
98-03	40	34	28	26	29	62	60	59	59	59	49	44	34	29	35	65	53	41	35	44	67	64	62	63	63	66	57	45	37	48				
04-07	59	56	43	44	46	77	75	72	72	73	61	58	46	44	49	71	67	50	53	55	81	79	75	75	76	72	68	53	54	57				
08-09	22	17	12	10	13	55	52	48	47	49	46	39	28	18	29	48	41	24	26	27	65	62	55	56	57	60	54	37	33	40				
10-13	16	12	8	6	8	46	45	41	41	42	39	34	22	15	24	40	31	18	20	20	58	55	49	52	51	53	47	32	28	35				
Mean	37	32	25	23	26	61	59	56	56	57	49	44	33	28	35	58	50	36	34	39	68	66	61	62	63	64	57	42	39	46				

Sources: HMDA, CoreLogic, and matched HMDA and CoreLogic data.

Notes: The analysis is limited to owner-occupied purchase mortgage applications. B = black; H = Hispanic; W = non-Hispanic white; A = Asian; T = all races and ethnicities.

The RDR Consistently Shows Tighter Credit in the Conventional Channel Than the Government Channel

At the time of loan origination, a borrower may choose either of two execution channels: government or conventional. The latter includes GSE, bank portfolio, and private-label securities executions.⁸

The government channel traditionally has had the broader credit box and higher pricing than the conventional channel, and it has been used disproportionately by LCP consumers. ODR results confirm that this observation is true before the financial crisis. However, after the crisis, the order reversed: the conventional channel appeared to have lower denial rates than the government channel (see table 2 and curves C and G in figure 1.A). This result is counterintuitive; it is a well-accepted fact that the conventional channel has much tighter underwriting standards and lower pricing.

Figure 1.E shows the ratio between the two ODRs of the conventional and the government channels, which reads as the relative tightness between the two channels. It shows that the denial rate for the conventional channel was 3.2 times tighter than the government channel in 1998, dropped steadily to only 1.1 times tighter in 2004, picked up to 1.6 times tighter in 2006, and dropped again after the financial crisis, making the ODR lower for the conventional channel than for the government each year since 2009. In 2013, the ODR results suggest that the government channel was 1.4 times tighter than the conventional channel.

Again, changes in loan applicants' credit profiles can explain the counterintuitive results. The average shares of LCP applicants in the conventional channel are 44, 55, and 20 percent, respectively, for the pre-bubble, bubble and post-crisis periods. These numbers are 63, 76, and 51 percent, respectively, for the government channel. Post-crisis, the conventional channel apparently discouraged more LCP consumers from applying for mortgages than the government channel, leading to fewer of them being rejected by the conventional channel than the government channel. This analysis again shows how the ODR leads to false impression of market tightness between channels over time.

The RDR shows more intuitive results. Curves C and G in figure 1.D show the RDRs of the conventional and the government channel, respectively. Notice the spread between the two curves: the conventional channel always has a higher RDR than the government channel, but the two curves have the least difference in the bubble years.

Figure 1.F shows the ratio between the two RDRs of the two channels: the conventional channel was 4.1 times tighter than the government channel in 1998, dropped to 1.6 and 1.8 times tighter in 2004 and 2005, then picked up and stayed 2.2 times tighter after the crisis. In 2013, LCP applicants

were twice as likely to be denied by conventional channels as by government channels. On average, during the pre-bubble and the post-crisis period, LCP applicants were two to four times more likely to be denied by the conventional channels than by the government channels. Even in the peak of the boom years, with the popularity of private-label securities in the conventional channel, LCP applicants were 1.6 times as likely to be denied by the conventional channels as by the government channels.

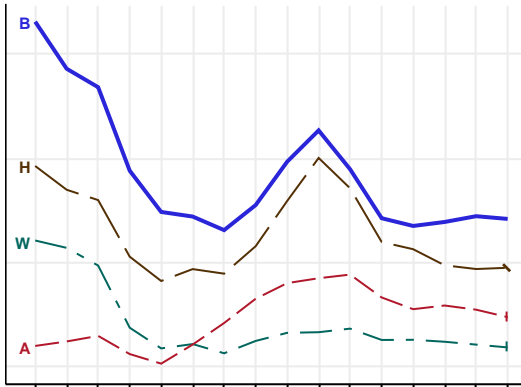
The RDR Shows Much Smaller Racial and Ethnic Gaps in Denial Rates

Research has made the case that minorities have not had the same access to the credit market as their white counterparts (Munnell et al. 1996).⁹ Our ODR results support this view: it is consistently highest for black applicants, followed by Hispanics. Non-Hispanic white and Asian applicants tend to have much lower ODR than the other two groups. On average over the 16 years, the ODR is 29 percent for black applicants, 23 percent for Hispanic applicants, 14 percent for non-Hispanic white applicants, and 15 percent for Asian applicants (see table 2 and figure 2.A and 2.E). Black, Hispanic and Asian applicants are 2.1, 1.7, and 1.2 times more likely to be denied by lenders than non-Hispanic white applicants.

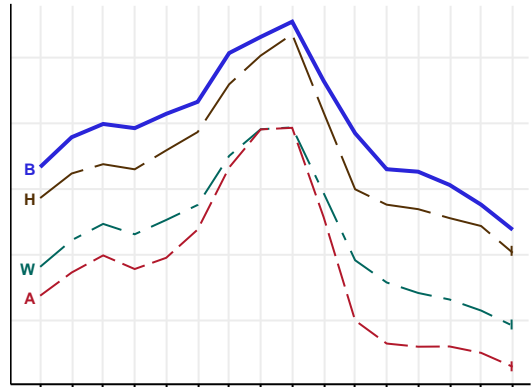
FIGURE 2

Denial Rates and Share of LCP Borrowers and Applicants by Race and Ethnicity

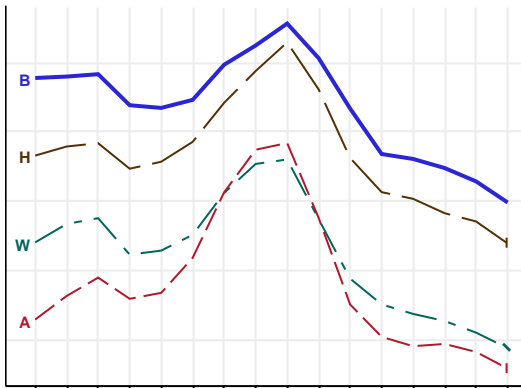
A: tradition denial rate (ODR)



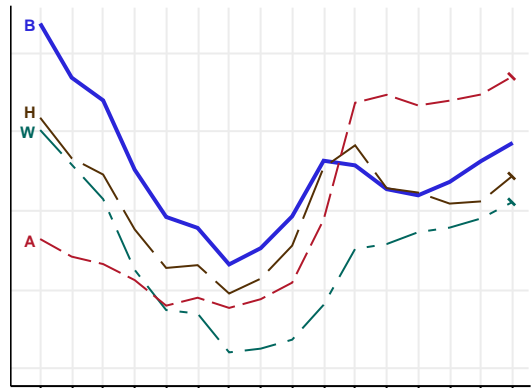
B: share of LCP borrowers



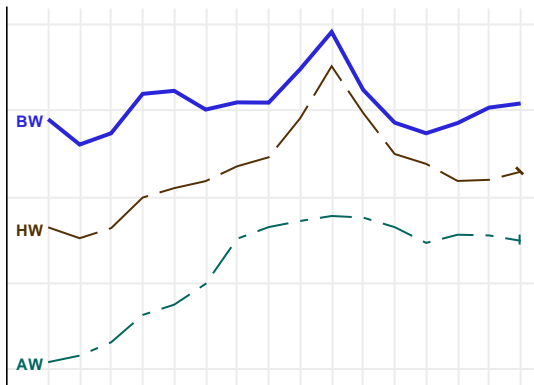
C: share of LCP applicants



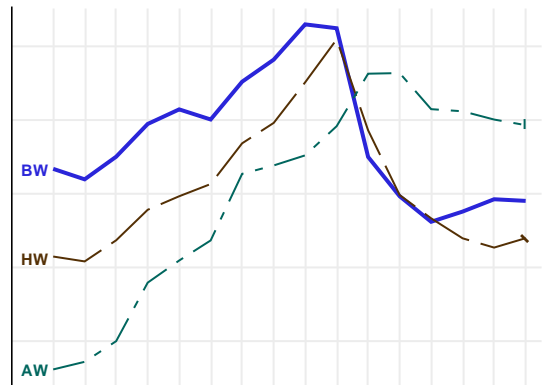
D: real denial rate (RDR)



E: ODR ratios



F: RDR ratios.



Sources: CoreLogic, HMDA, matched HMDA and CoreLogic data, and author calculations.

Notes: A = Asian; B = black; H = Hispanic; W = non-Hispanic white; AW = ratio between A and W; BW = ratio between B and W; HW = ratio between H and W.

Does this finding indicate that black and Hispanic applicants have less access to mortgage credit than their white and Asian counterparts? Not necessarily, since the ODR doesn't consider the credit profile of the applicants. For example, if the share of LCP applicants is two times higher for black applicants than for white applicants, then the observed higher denial rate for the former could be explained entirely by the higher proportion of black LCP applicants.

In fact, over our 16-year study period, the share of LCP applicants has been consistently higher in the black and Hispanic groups than in the Asian and non-Hispanic white groups. The average share of LCP applicants among black, Hispanic, non-Hispanic white, and Asian applicants over the 16 years are about 64, 57, 42, and 39 percent, respectively (table 3 and figure 2.C). So, the average shares of LCP applicants among black and Hispanic applicants are about 1.5 and 1.4 times higher than for non-Hispanic white applicants.

By measuring denial rates exclusively for LCP applicants, the RDR shows much smaller racial and ethnic gaps: average denial rates over the 16 years are 45 percent for blacks, 41 percent for Hispanics, 34 percent for non-Hispanic whites, and 40 percent for Asians (see table 2 and figure 2.D). Black, Hispanic, and Asian LCP applicants are only about 1.3, 1.2 and 1.2 times more likely to be denied by lenders than non-Hispanic white LCP applicants. Also, these gaps have been narrowing over time.

Therefore, the latest RDR numbers show that racial gaps are not the major challenge on credit accessibility. The key challenge is that the mortgage market is excluding half the borrowers with weaker credit profiles, including minorities.

The Government Channel Is the Main Credit Provider for LCP Applicants

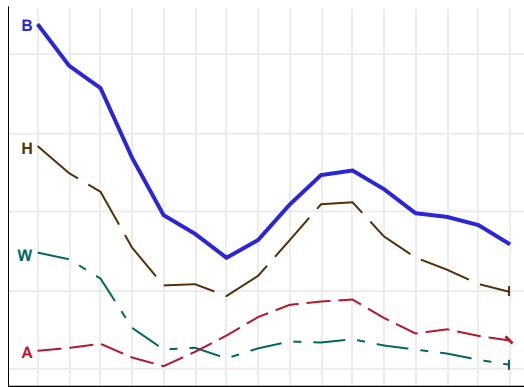
We have discussed channel differences and racial gaps on denial rates separately. Below we examine channel differences by racial and ethnic groups, and racial and ethnic gaps by channels.

Within the conventional channel, on average over the 16-year period, the ODR is approximately 34 percent for black applicants, 26 percent for Hispanics, and 15 percent for both non-Hispanic whites and Asians (see table 2 and figure 3.A). These numbers are 18, 16, 11, and 14 percent, respectively, for the government channel (see table 2 and figure 4.A). Based on these numbers, blacks are twice as likely to be denied for conventional loans as for government loans. The same ratio is much lower for non-Hispanic white and Asian applicants, which seems to suggest the conventional channel has a much higher racial disparity than the government channel.

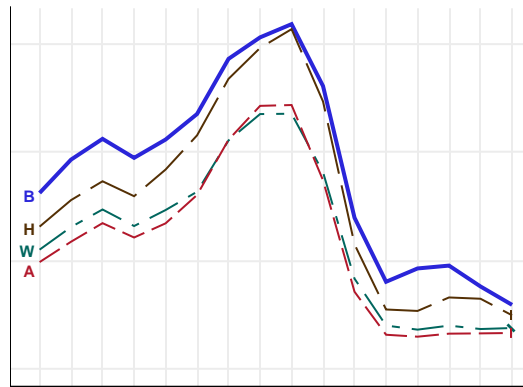
FIGURE 3

Denial Rates and Share of LCP Borrowers and Applicants: Race and Ethnicity of the Conventional Channel

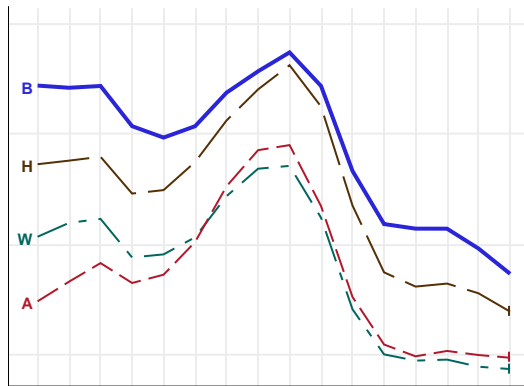
A: tradition denial rate (ODR)



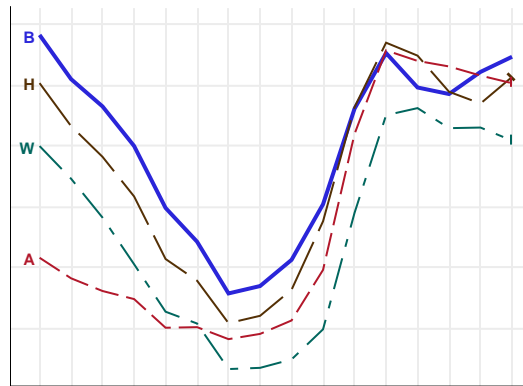
B: share of LCP borrowers



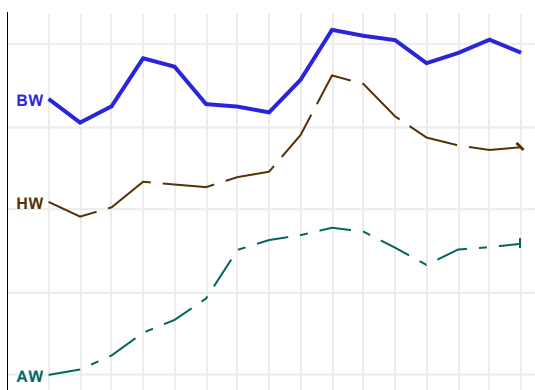
C: share of LCP applicants



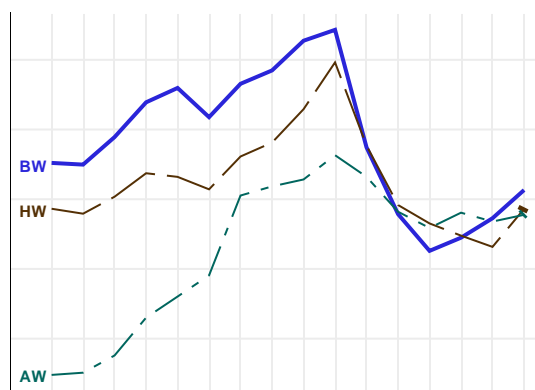
D: real denial rate (RDR)



E: ODR ratios



F: RDR ratios.



Sources: CoreLogic, HMDA, matched HMDA and CoreLogic data, and authors' calculations.

Notes: A = Asian; B = black; H = Hispanic; W = non-Hispanic white; AW = ratio between A and W; BW = ratio between B and W; HW = ratio between H and W.

Closer inspection reveals that the pattern stems not from racial discrimination but from higher variation in the share of LCP applicants by race and ethnicity in the conventional channel than in the government channel. On average within the conventional channel over the 16 years, 58 percent of black applicants, 50 percent of Hispanic applicants, 36 percent of non-Hispanic white applicants, and 34 percent of Asian applicants are LCP. The corresponding numbers for the government channel are 68 percent, 66 percent, 61 percent, and 62 percent.

By looking exclusively at LCP applicants, we see that the channel difference on denial rate is about the same across different racial and ethnic groups. Within the conventional channel, on average over the 16-year period, black, Hispanic, non-Hispanic white, and Asian LCP applicants are 60, 56, 46, and 48 percent, respectively, likely to be denied a conventional mortgage (see table 2 and figure 3.D). These numbers are only 28, 25, 18, and 23 percent for the government channel (see table 2 and figure 4.D). These RDR results clearly show that LCP applicants from every racial and ethnic group are about two to three times more likely to be denied by the conventional channel than by the government channel. In other words, the government channel serves the credit needs of LCP consumers. Moreover, when looking at RDRs, the racial differences substantially converge, indicating that much of the differences in denial rates reflect differences in credit profiles.

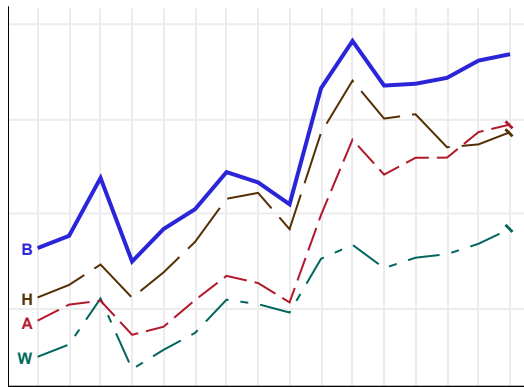
Looking at the post-crisis period, the conventional channel rejects 63 to 71 percent of LCP applicants, including minorities. In contrast, the government channel rejects 27 to 39 percent of LCP applicants, again including minorities.

After the financial crisis, the conventional channel clearly closed its door to the vast majority of LCP consumers. The government channel has become the major channel through which these consumers receive loans. However, even the government channel is rejecting more applicants than during the pre-bubble and bubble periods. The super-tight credit box for LCP consumers reduces the number of buyers and, thereby, lengthens the housing recovery. When affordable mortgage payments relative to income make homeownership an attractive proposition, this closed door means an excellent wealth-building tool is out of reach for many consumers with lower credit profiles.

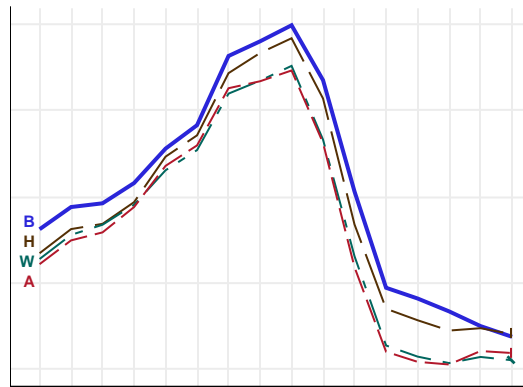
FIGURE 4

Denial Rates and Share of LCP Borrowers and Applicants: Race and Ethnicity of the Government Channel

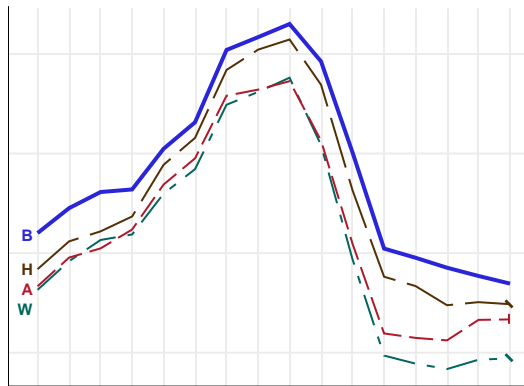
A: tradition denial rate (ODR)



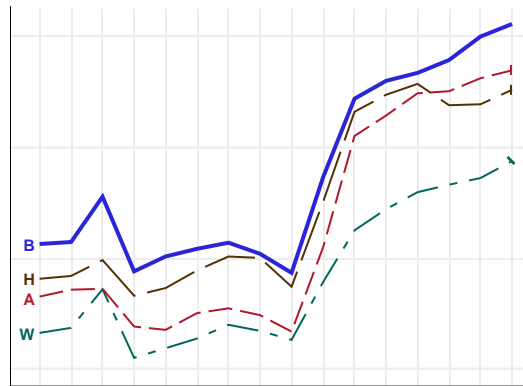
B: share of LCP borrowers



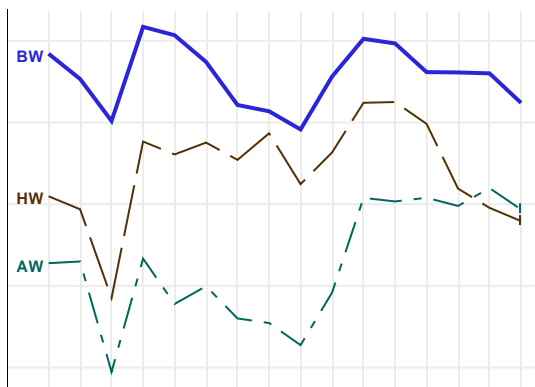
C: share of LCP applicants



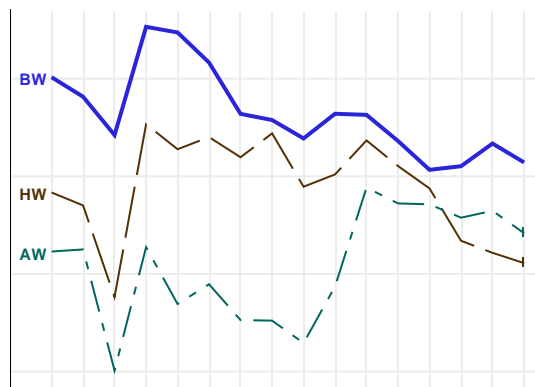
D: real denial rate (RDR)



E: ODR ratios



F: RDR ratios.



Sources: CoreLogic, HMDA, matched HMDA and CoreLogic data, and authors' calculations.

Notes: A = Asian; B = black; H = Hispanic; W = non-Hispanic white; AW = ratio between A and W; BW = ratio between B and W; HW = ratio between H and W.

Conclusions

Access to sustainable mortgage credit can play a critical role in a family's pursuit of financial prosperity. Yet our ability to measure access to such credit has been limited. This paper addresses the limitations of mortgage application denial rate as a measure of credit accessibility. By measuring denial rates exclusively for low-credit-profile applicants, the real denial rate shows more intuitive trends on credit accessibility through time, a consistently tighter credit box for the conventional channel than the government channel, and much smaller racial and ethnic gaps on denial rates. The real denial rate provides policymakers with powerful new tools to assess credit accessibility over time and by demographic group and channels.

The real denial rate, as we have defined it, is imperfect: it makes no distinctions among low-credit-profile applicants. In addition, the real denial rate, like the traditional denial rate, fails to take into account another important way that people fail to access mortgage credit: they are deterred from applying in the first place. We address this limitation in another paper (Li et al. 2014). Even with these limitations, we believe the real denial rate is a much better measure of credit accessibility than the traditional, often-quoted observed denial rate.

Appendix

TABLE A.1

Probability of Being a Low-Credit-Profile Borrower, Calculated from the Expected Default Risk of the Loans (%)

Backend DTI	CLTV	Non-Risky Loan Products							Risky Loan Products						
		FICO							FICO						
		Average	>740 (700,740]	(660,700]	(620,660]	(580,620]	≤580	Average	>740 (700,740]	(660,700]	(620,660]	(580,620]	≤580		
Average	Average	18	6	16	24	38	57	80	81	49	76	87	93	95	96
	(0,68]	3	0	2	5	13	22	39	21	4	18	28	38	42	58
	(68,78]	9	2	9	16	25	33	58	51	21	45	60	72	70	84
	(78,82]	12	4	12	19	28	34	54	74	40	65	79	94	91	99
	[82,90]	18	7	17	24	32	43	69	89	62	89	95	88	95	100
	(90,95]	19	7	15	21	32	44	69	82	58	76	80	87	100	100
	>95	56	29	42	52	70	93	100	97	86	94	99	100	100	100
Full Doc & (0,30)	Average	6	0	3	9	22	41	63	58	13	35	60	83	94	96
	(0,68]	1	0	0	0	6	15	30	11	0	6	11	31	45	58
	(68,78]	2	0	0	4	11	22	39	26	3	13	30	45	64	86
	(78,82]	2	0	1	5	12	21	34	42	9	26	45	70	98	98
	[82,90]	5	0	3	8	18	29	51	71	22	46	59	71	86	100
	(90,95]	9	0	4	11	23	35	55	68	23	43	63	76	100	100
	>95	36	8	18	32	59	92	100	84	33	59	86	100	100	100
Full Doc & [30,40)	Average	12	1	6	15	29	50	69	74	26	51	72	89	97	97
	(0,68]	1	0	0	1	9	17	27	19	1	11	21	40	43	50
	(68,78]	4	0	2	7	16	27	42	38	9	23	35	55	76	85
	(78,82]	5	0	4	10	17	27	40	57	18	37	52	76	100	100
	[82,90]	8	1	5	12	21	33	53	76	27	50	68	76	84	100
	(90,95]	12	2	6	14	25	37	55	74	33	53	65	77	100	100
	>95	41	12	21	38	66	98	100	89	47	69	91	100	100	100
Full Doc & [40,50)	Average	17	4	11	21	35	54	71	86	40	65	85	93	98	98
	(0,68]	2	0	0	4	11	18	27	27	3	15	28	38	50	56
	(68,78]	7	0	5	12	21	28	40	51	13	31	47	64	77	87
	(78,82]	10	2	8	15	23	34	45	73	27	47	65	85	100	100
	[82,90]	15	4	9	18	28	40	64	85	37	58	74	78	90	100
	(90,95]	17	6	11	19	31	43	60	83	43	59	70	81	100	100
	>95	51	20	30	47	73	100	100	96	65	83	100	100	100	100
Full Doc & ≥50	Average	17	5	13	23	40	52	62	88	43	71	87	95	99	97
	(0,68]	3	0	0	5	14	23	27	35	9	24	37	50	63	61
	(68,78]	9	1	8	14	26	34	41	60	15	45	63	84	84	84
	(78,82]	11	3	10	18	29	34	37	72	31	52	63	79	100	100
	[82,90]	19	7	13	24	38	47	56	91	50	78	83	85	97	100
	(90,95]	22	10	16	26	39	52	61	91	60	71	81	99	100	100
	>95	53	23	33	51	78	100	100	98	74	90	100	100	100	100
Low or No Doc	Average	30	13	30	41	55	73	93	83	57	82	89	94	90	93
	(0,68]	4	0	5	11	21	34	59	22	5	20	29	38	40	58
	(68,78]	16	5	19	29	41	49	82	54	26	50	64	75	68	83
	(78,82]	21	10	22	33	49	53	80	78	48	71	84	98	84	99
	[82,90]	35	19	36	46	53	62	86	92	71	96	100	91	99	100
	(90,95]	36	21	36	42	50	61	99	84	67	83	84	90	100	100
	>95	69	51	65	65	71	88	100	100	100	100	100	100	100	100

Sources: SFPD and CoreLogic.

Notes

1. HMDA is considered the “universe” of mortgage applications and originations because federal law requires that almost all mortgage applications, except to some small lenders, be reported in HMDA. See Avery, Brevoort, and Canner (2007) and McCoy (2007) for detailed discussion on HMDA’s coverage of residential mortgages.
2. Though a few proprietary mortgage databases, such as the CoreLogic data, collect information on originated loans, HMDA is the only source of mortgage application data, which contains mortgage applicant’s income, loan amount, race and ethnicity, and the outcome of the application. However, HMDA do not have information on common risk factors such as credit score, LTV, DTI, and loan products. Therefore, applicant’s credit profile is unknown from HMDA data.
3. CoreLogic, Inc., is a US corporation providing financial, property, and consumer information, analytics, and business intelligence. According to CoreLogic’s data dictionary, its loan database covers approximately 75 percent to 90 percent of all residential mortgages including outstanding and terminated loans, although the percentage varies by market. As of March 2013, the database covers approximately 85 percent of all outstanding residential mortgages.
4. CoreLogic and all other proprietary mortgage database do not have borrower’s demographic information. HMDA does not have borrower’s credit profile information. To supplement each other, we matched HMDA origination data to CoreLogic’s proprietary loan-level databases. To expand the size of the matched database beyond unique matches, we assigned weights to each matched HMDA-CoreLogic loan pair, to reflect how close the match is, and supplemented information in either database with information from the other using this weight. See Li et al. (2014) for details. To make the matched loans representative to the original HMDA loans on any combination of important variables, each matched loan is weighted to reflect the same joint distribution as the original HMDA loans on the combination of the following variables: year of origination, Bureau of Economic Analysis regions, borrower race, ethnicity, and income, loan amount and channel (conventional vs. government). Borrower income is first divided by median MSA income then transformed into ordinal variables. Loan amount is first divided by borrower income then transformed into ordinal variables. Therefore, with this weighting, the matched loans should perfectly represent the whole population of the original HMDA loans, in terms of the joint distribution on the above variables.
5. Limiting analysis to this group of loans and loan applications allows a more accurate comparison over time. The underwriting for a non-owner-occupied home mortgage is sufficiently different that we excluded these loan applications from our analysis. Similarly, a refinance application is heavily a function of interest rates, and various streamlined programs have allowed loans to refinance that would not meet prevailing credit criteria for a new loan, on the grounds that a refinance helps the borrowers and reduces the probability of default of the loan, to the benefit of the holder of the risk.
6. The potential outcomes of a loan application are dealt with as follows: application or preapproval request denied = denied; application or preapproval request approved but not accepted = approved; loan originated = approved. Loans purchased by a financial institution at a HMDA reporting year are excluded from the analysis.
7. Since only originated HMDA loans can be matched with CoreLogic loans, we assume approved but not originated applications have the same share of LCP members as originated loans.
8. The government channel consists of FHA, VA, and USDA loans guaranteed by government agencies. All other loans belong to the conventional channel. Within the conventional channel, after the lender originates the loan, it can be securitized with GSEs or private-labeled securities, or be kept in the financial institution’s portfolio. For loans going to the conventional channel, HMDA data do not specify which guarantor the loan will go to at the application stage.
9. In this paper, we adopt a hierarchical approach to define race and ethnicity jointly. For HMDA data reported before 2004, the jointly reported field on applicant’s race and ethnicity is used directly for the definition. For 2004 and after, we adopted the same approach used by Avery, Canner, and Cook (2005) and Avery, Brevoort, and Canner (2006): black trumps Hispanic, Hispanic trumps Asian, Asian trumps other minorities, and other

minorities trumps white, in any one of the five race fields and one ethnicity field. Coapplicant's race and ethnicity are ignored when defining applicant's race and ethnicity. See Avery, Brevoort, and Canner (2007) for race and ethnicity definition issues.

References

- Avery, Robert B., Glenn B. Canner, and Robert E. Cook. 2005. "New Information Reported under HMDA and Its Application in Fair Lending Enforcement." *Federal Reserve Bulletin* 91: 344.
- Avery, Robert B., Kenneth P. Brevoort, and Glenn B. Canner. 2006. "Higher-Priced Home Lending and the 2005 HMDA Data." *Federal Reserve Bulletin* 92: A123-66.
- . 2007. "Opportunities and Issues in Using HMDA Data." *Journal of Real Estate Research* 29 (4): 351-80.
- Li, Wei, and Laurie S. Goodman. 2014. "Measuring Credit Availability Using Ex-Ante Probability of Default." Washington, DC: Urban Institute.
- Li, Wei, Laurie S. Goodman, Ellen Seidman, Jim Parrott, Jun Zhu, and Bing Bai. 2014. "Measuring Mortgage Credit Accessibility." Washington, DC: Urban Institute.
- McCoy, Patricia A. 2007. "The Home Mortgage Disclosure Act: A Synopsis and Recent Legislative History." *Journal of Real Estate Research* 29 (4): 381-97.
- Munnell, Alicia H., G. M. Tootell, L. E. Browne, and J. McEneaney. 1996. "Mortgage Lending in Boston: Interpreting HMDA Data." *American Economic Review*, 25-53.

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Before joining Urban in 2013, Goodman spent 30 years as an analyst and research department manager at a number of Wall Street firms. From 2008 to 2013, she was a senior managing director at Amherst Securities Group, LP, a boutique broker/dealer specializing in securitized products, where her strategy effort became known for its analysis of housing policy issues. From 1993 to 2008, Goodman was head of Global Fixed Income Research and Manager of US Securitized Products Research at UBS and predecessor firms, which was ranked first by *Institutional Investor* for 11 straight years. She has also held positions as a senior fixed income analyst, a mortgage portfolio manager, and a senior economist at the Federal Reserve Bank of New York.

Goodman was inducted into the Fixed Income Analysts Hall of Fame in 2009. She serves on the board of directors of MFA Financial and is a member of the Bipartisan Policy Center's Housing Commission, the Federal Reserve Bank of New York's Financial Advisory Roundtable, and the New York State Mortgage Relief Incentive Fund Advisory Committee. She has published more than 200 articles in professional and academic journals, and has coauthored and coedited five books. Goodman has a BA in mathematics from the University of Pennsylvania and a MA and PhD in economics from Stanford University.



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